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Research Paper

GameMoodNet: Toward Adaptive Gaming via Multimodal Deep Affective Intelligence Frameworks

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ABSTRACT

In recent years, understanding player behavior and emotional states during gameplay has become an important research area in game analytics and human computer interaction. Emotional state detection enables game designers and researchers to analyse player engagement, improve user experience, and develop adaptive gaming environments. Traditionally, emotional behavior analysis in games relied on manual approaches such as questionnaires, player observation, and basic statistical analysis. These methods were time-consuming, less accurate, and unable to provide real-time insights into player emotions and behavior during gameplay. To address these limitations, this research proposes a Hybrid Fuzzy Boosting Architecture for Accurate Emotional State Detection in Real-Time Gameplay. The system is implemented as a web-based application using the Django web framework. Machine Learning (ML) techniques are used to analyse gameplay behavior data and predict emotional states efficiently. The research utilizes several ML algorithms including K-Nearest Neighbours (KNN), Random Forest (RF), Support Vector Machine (SVM), and a proposed hybrid model Fuzzy Neuro Boosting (FNB) model that combines Fuzzy Neural Network with Histogram Gradient Boosting (FNN-HGB). These algorithms are trained and evaluated using both classification and regression tree (CART) techniques to classify player behaviour (play_behavior) and predict engagement intensity (activity_level). Among the evaluated models, the proposed hybrid FNB model achieves higher prediction accuracy compared to traditional ML classifiers, demonstrating improved performance in handling complex and noisy gameplay data. The system also includes modules such as user authentication, exploratory data analysis, model training, performance comparison, and real-time prediction. By integrating ML models with a Django-based web interface, the developed system provides an efficient platform for analysing gameplay behaviour and predicting emotional states, thereby supporting better decision-making and improved player experience in modern gaming environments.

Keywords: Emotional State Detection, Machine Learning, Fuzzy Neuro Boosting (FNB), Django Framework, Data Analysis.

1. INTRODUCTION

Video games are a comprehensive entertainment platform used generally for children and adolescents, but yielding a growing research field to understand human motivations and learning processes. People usually think violent video games could yield more aggressive behavior in young game players. However, a meta-analysis reported that only a tiny group presented the violent effects of long-time video game exposure. Contrary to many beliefs, several video games helped treat medical conditions, teach, and improve coordination skills and even cognitive behavior. These types of video games are

usually called Serious Games. Thus, recent findings suggest that these therapeutic video games improve children's well-being by helping them overcome real-life issues, producing different beneficial scenarios that trigger emotional responses as shown in Fig. 1.

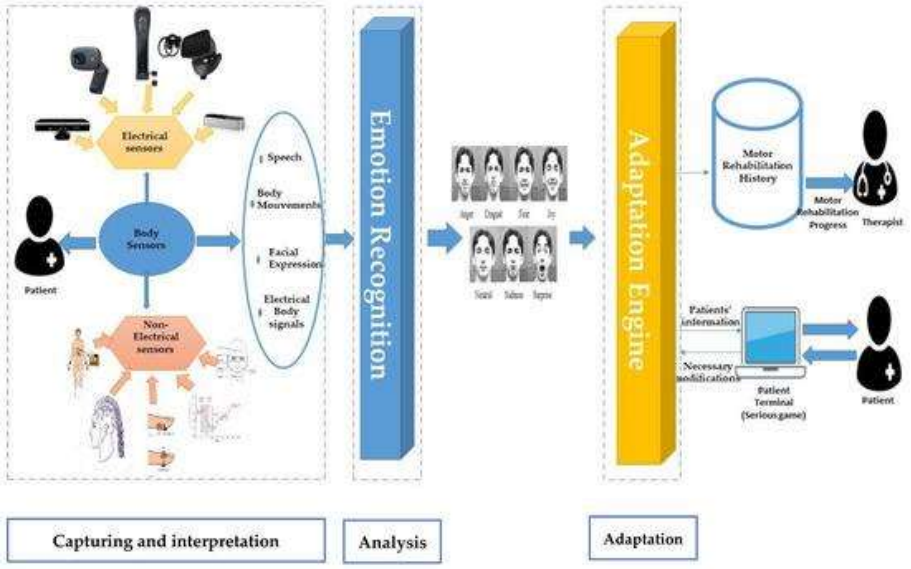


Fig. 1: A personalized game platform based on emotion recognition.

Furthermore, serious games presented a less invasive but enjoyable learning process, achieving attention, motivation, and extensive training seasons. However, other games developed for physical movements, such as exergames, require players' strength, balance, and flexibility.

2. LITERATURE SURVEY

Matsouliadis et al. [1] developed two serious games using Unreal Engine 5 and researched the integration of speech emotion recognition within real-time game environments. The games were designed to elicit diverse emotional responses and collect players' speech data for improving SER models. They evaluated player engagement, emotional expression, and user experience to assess the effectiveness of serious games for data collection. They also investigated technical challenges such as latency and its impact on gameplay and enjoyment.

Cruz-Vazquez et al. [2] investigated affective computing by developing an emotion recognition system based on EEG signals. They proposed a deep learning model trained on a proprietary EEG dataset and explored advanced data transformation techniques, including Fourier Neural Networks and quantum rotations, to improve emotion separability. They evaluated the performance of a convolutional neural network combined with these transformations and achieved high classification accuracy, particularly for sad emotions. The study demonstrated that integrating such transformations can enhance overall EEG-based emotion recognition performance.

Wu et al. [3] conducted a comprehensive review of multimodal emotion recognition systems that integrate speech, visual, and textual modalities. They analyzed MER from a biomimetic perspective, emphasizing bio-inspired multisensory fusion for emotion understanding. The study reviewed system architectures, feature extraction methods, and fusion strategies while highlighting key advancements. They also identified open challenges and discussed future research directions to improve robustness, generalizability, and real-world applicability of MER systems.

Majkowski et al. [4] evaluated the practical applicability of speech-based emotion recognition technologies for human–computer interaction systems. They analyzed English and Polish emotional speech datasets using a wide range of acoustic features and ML models, including CNNs, LSTMs, and cubic SVMs. They investigated both multi-class and paired-emotion classification in a subject-independent setting. The results showed limited performance for recognizing many emotions simultaneously but strong effectiveness in distinguishing specific emotion pairs for targeted HCI applications.

Song et al. [5] proposed a multimodal emotion recognition framework that combined facial expressions and speech-derived text to model dynamic emotional changes in conversations. They constructed emotion sequences from dialogue utterances using the MELD dataset and analyzed emotional transitions and shifts across conversations. The approach fused facial and speech-based emotion information to capture the contextual flow of emotions rather than single, static judgments. Experimental results showed that this method better represented emotional dynamics and outperformed existing approaches.

Emotion recognition is essential for enhancing human–machine interaction and developing empathetic, adaptive systems. Current emotion recognition technologies include facial expression analysis, voice analysis, and physiological signal analysis [6, 7]. However, methods based on facial and vocal cues can be consciously manipulated by users, reducing recognition accuracy. Consequently, physiological signals, such as those obtained through electroencephalography (EEG), offer a more reliable alternative by capturing brain electrical activity directly at its source [8].

This review covers research on multimodal emotion recognition spanning the past two decades, focusing on key areas such as system architecture, feature extraction techniques, and fusion strategies [9]. Recent surveys provide valuable but partial snapshots of the field: some emphasize dataset curation and classical fusion pipelines, others concentrate on deep-learning advances since 2020 or on conversation-level affect modeling [10]. A few broaden the scope to physiological sensing [11] or present high-level trend statistics without methodological detail [12]. The present review differs in three respects. First, it spans 2011–2025 and is selected through a PRISMA-compliant process, guaranteeing transparent coverage. Second, it cross-links modalities, algorithms, and application scenarios within a unified three-dimensional taxonomy, something earlier reviews omit. Third, it couples qualitative synthesis with quantitative comparisons, revealing how dataset characteristics drive fusion choices and performance. These contributions position our work as a holistic complement to the specialized reviews above [13].

A rapid bibliometric scan of the 103 studies included in this review uncovers two salient trends. First, publication volume has exploded almost four-fifths of all papers (82/103 ≈ 80%) appeared in or after 2019, with 2023 emerging as the single most productive year (n = 19), followed by 2024 (n = 14). Second, research output remains geographically concentrated China (~31%), the United States (~18%), and the EU-27 (~24%) together account for close to three-quarters of the literature, mirroring the distribution highlighted in recent large-scale surveys [14, 15].

3. PROPOSED METHODOLOGY

The methodology adopted in this research establishes a structured and data-driven approach for analysing player behaviour and emotional states in real-time gameplay environments. The study follows a systematic pipeline that begins with data collection and preprocessing, followed by feature preparation, ML-based classification and regression, and performance evaluation as demonstrated in Fig. 2. Multiple ML models are employed under a unified CART-based framework to ensure

consistency, interpretability, and reliability of predictions. The methodology supports both offline model training and real-time inference, enabling effective behavioural analysis across diverse gameplay scenarios. A web-based interface facilitates user interaction, visualization, and prediction management. Model persistence and retraining mechanisms further enhance adaptability to evolving gameplay patterns, ensuring sustained analytical performance over time.

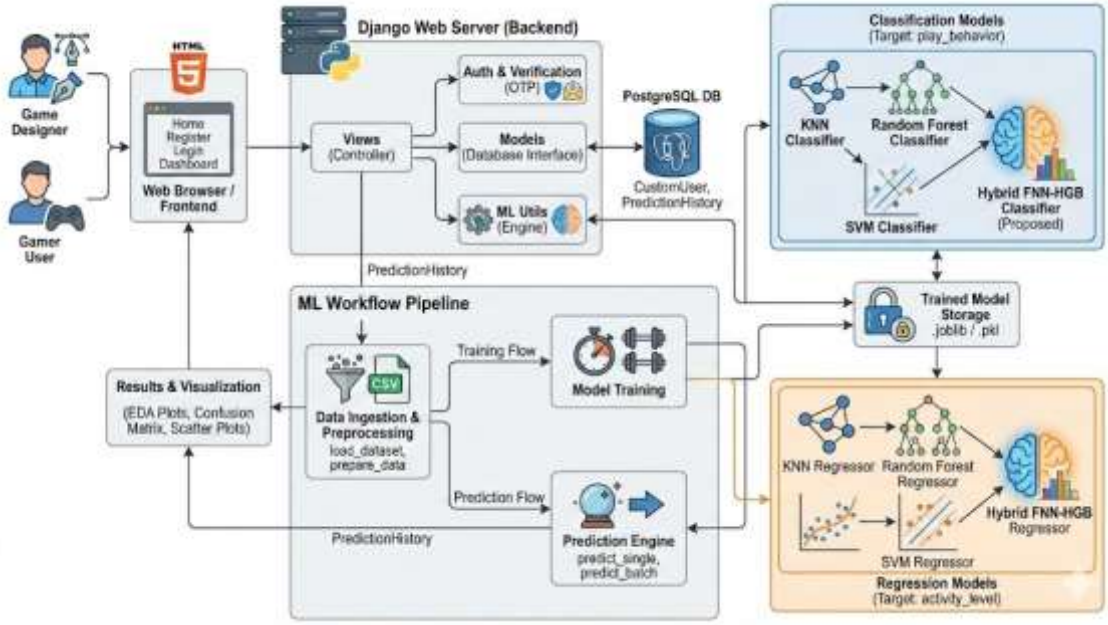


Fig. 2: System architecture of game mode net.

User Interface (Web Browser)

- The user interacts with the system through a browser-based graphical interface.
- The interface allows users to perform actions such as registration, login, dataset upload, exploratory data analysis viewing, single prediction, batch prediction, and model training.
- All user actions are translated into HTTP requests and forwarded to the Django web server.
- Prediction results, evaluation metrics, and visualizations are displayed dynamically on the interface.

Django Web Server (views.py)

- The Django backend handles all incoming requests from the user interface.
- It manages authentication, authorization, dataset loading, prediction workflows, and result rendering.
- The server coordinates communication between the database, ML models, and visualization modules.
- It also triggers model training and evaluation processes when requested by the user or administrator.

Database Layer (Prediction History & User Data)

- The database stores persistent system data required for operation.
- It maintains records of registered users, prediction history, model outputs, and interaction logs.
- Prediction inputs and results are stored to support tracking, auditing, and future analysis.
- The database communicates with the Django server for secure and efficient read/write operations.

Raw Data Input (Gameplay Dataset)

- The gameplay dataset serves as the primary input source for the system.
- It contains numerical and categorical features derived from player interactions, gameplay events, and performance metrics.
- The dataset includes the target variables play_behavior and activity_level.
- Uploaded data is forwarded directly to the preprocessing and feature preparation module.

Data Preprocessing and Feature Preparation (ml_utils.py)

- The raw dataset undergoes cleaning, normalization, and encoding to ensure consistency.
- Numerical features are scaled using standardization techniques.
- Categorical features are encoded into numerical representations.
- A unified feature vector is generated and passed to all ML models for training and prediction.

ML Models (CART-Based Framework)

- The processed feature vectors are provided to multiple classification models:
  - KNN
  - RF
  - SVM
  - Hybrid FNB
- These models predict the categorical target variable play_behavior.
- CART-based decision logic ensures interpretability and consistency across model evaluations.
- For engagement estimation, CART-based regression models predict the continuous activity_level.

Model Evaluation and Comparison

- The system evaluates model performance using standard metrics such as accuracy, precision, recall, F1-score, MAE, RMSE, and R^2.
- Confusion matrices, ROC curves, and scatter plots are generated for visual analysis.
- Model-wise comparisons help identify the most effective model for gameplay behaviour recognition.

Prediction Output and Visualization

- Final predictions for play_behavior and activity_level are displayed on the user interface.
- Single prediction outputs provide immediate behavioural insights.
- Batch prediction outputs present results in tabular form for large datasets.
- All prediction results are logged in the database for future reference.

Model Retraining and Adaptation

- The system supports retraining of ML models when new data is introduced.
- Updated datasets are processed through the same preprocessing pipeline.
- Models are retrained to improve accuracy and adapt to evolving gameplay behaviour.
- Updated models and performance metrics are stored, completing the adaptive learning cycle.

FNB CART Model

The hybrid FNB model operates by combining fuzzy reasoning with CART-based gradient boosting to achieve accurate and robust behaviour prediction. It integrates the adaptive learning capability of FNN with the structured decision-making strength of Histogram Gradient Boosting trees. This hybrid design enables effective handling of uncertainty, non-linearity, and complex feature interactions present in gameplay data. Under a CART framework, the model maintains interpretability through tree-based decisions while benefiting from boosted ensemble learning. The fusion mechanism ensures reliable classification and regression performance across diverse gameplay scenarios.

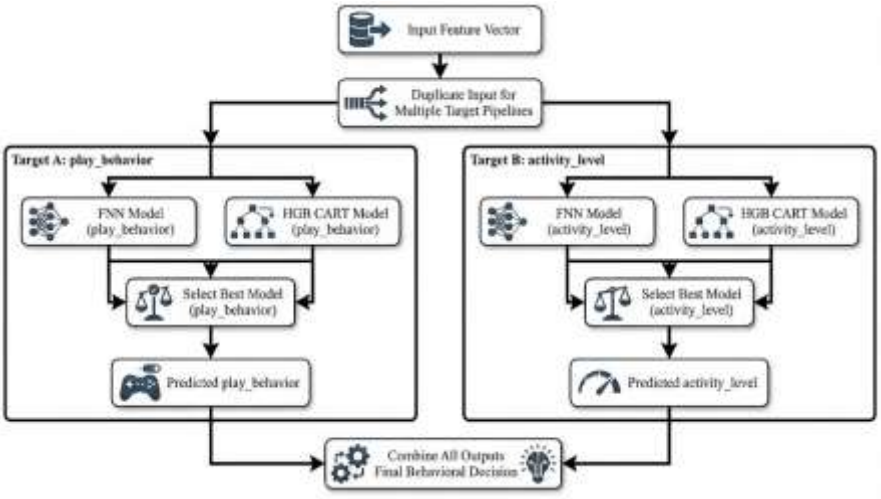


Fig. 3: Internal workflow FNB CART.

Fuzzy Input Representation: The pre-processed gameplay features are transformed into fuzzy representations using membership functions. This step captures uncertainty and gradual transitions in player behaviour. Fuzzy inputs allow the model to handle ambiguous and noisy gameplay patterns effectively.

FNN Processing: The fuzzy inputs are passed through the neural network layers to learn non-linear feature interactions. Hidden layers adaptively adjust weights based on fuzzy activations. This stage produces an intermediate representation enriched with behavioural semantics.

Histogram-Based Feature Binning: The learned feature representations are discretized into histogram bins. This reduces computational complexity and stabilizes learning. Histogram binning prepares the data for efficient CART-based tree construction.

CART-Based Gradient Boosting: Multiple shallow CART trees are trained sequentially using gradient boosting principles. Each tree focuses on correcting the errors of previous trees. This iterative refinement improves prediction accuracy and robustness.

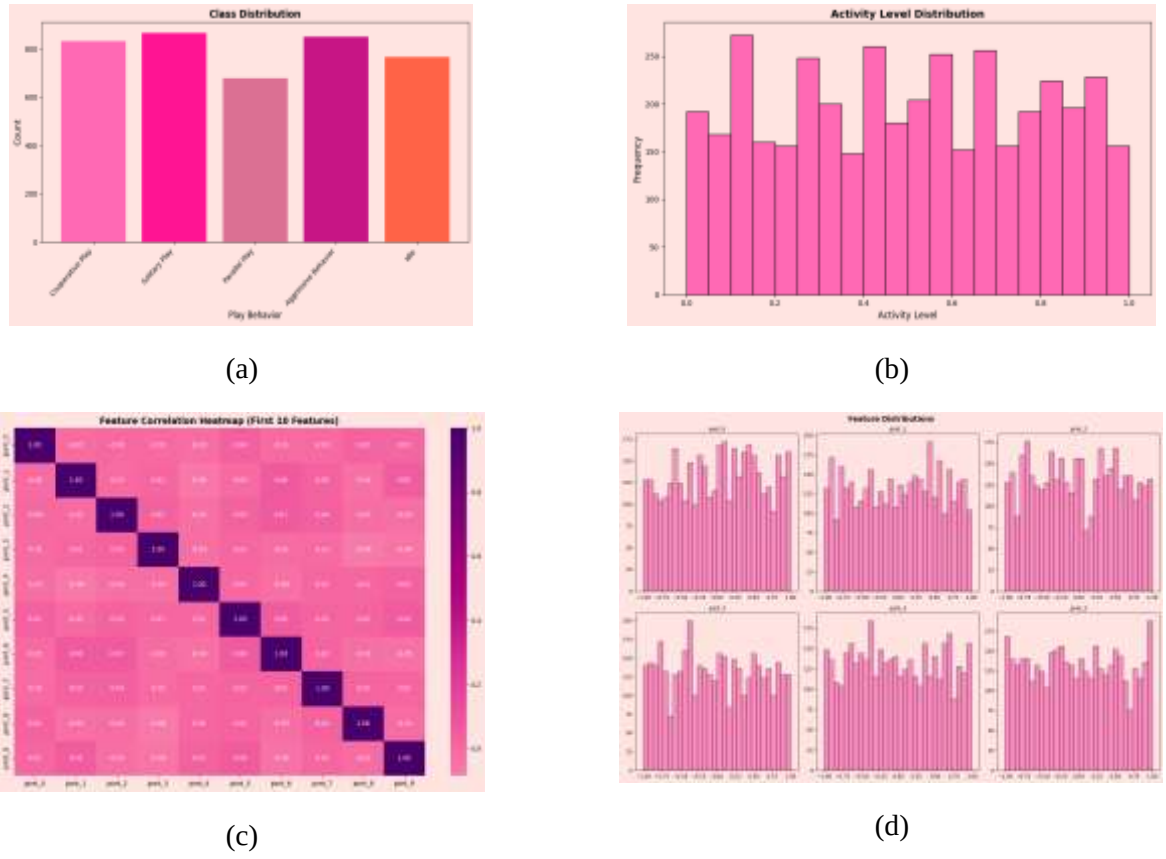
Prediction Aggregation: Outputs from all boosted CART trees are aggregated to produce final predictions. For classification, class scores are combined, while for regression, values are averaged. This aggregation ensures stable and reliable outputs.

CART-Aligned Decision Interpretation: The final decision is interpreted as the result of traversing multiple CART leaf regions. Feature importance and split contributions can be analysed for explainability. This alignment enables transparent and consistent interpretation of hybrid model decisions.

Advantages of the Hybrid FNN–HGB CART Model

- Improves prediction accuracy by combining neural learning and CART-based decision trees.
- Effectively handles uncertainty and noisy gameplay data through fuzzy reasoning.
- Provides better interpretability compared to pure deep learning models.
- Reduces model bias by selecting the best performer per target.
- Supports multi-target learning without interference between outputs.
- Suitable for real-time systems due to efficient CART-based boosting.
- Enhances robustness across diverse gameplay scenarios and player behaviours.

4. Result Description



(a) (b)

(c) (d)

Fig. 4: Data analysis on gameplay behavior dataset. (a) Bar plot. (b) Correlation heatmap. (c) Histogram. (d) Histogram.

Fig. 4 presents the exploratory data analysis performed on the gameplay behavior dataset used in this research. The visualization includes four different plots that illustrate the distribution and relationships among important dataset attributes.

Fig 4 (a) shows a bar plot representing the distribution of the play_behavior classes in the dataset. The bar chart displays the number of samples available for each behavior category, which provides a clear understanding of how the dataset is distributed across different behavioral labels used for classification.

Fig 4 (b) illustrates the correlation heatmap generated from the numerical features of the dataset. The heatmap is created using correlation values computed through DataFrame.corr() and visualized using seaborn.heatmap(). This plot highlights the relationships between selected features and helps identify patterns among gameplay attributes such as body joint coordinates, sensor measurements, and other numerical variables.

Fig 4 (c) and Fig 9.3(d) present histogram plots showing the distribution of selected numerical features from the dataset. These histograms display the frequency distribution of feature values and provide insights into the variation and spread of gameplay attributes across different samples. The histogram plots support the analysis of feature characteristics and contribute to understanding the dataset structure before applying ML models for behavior classification and activity level prediction.

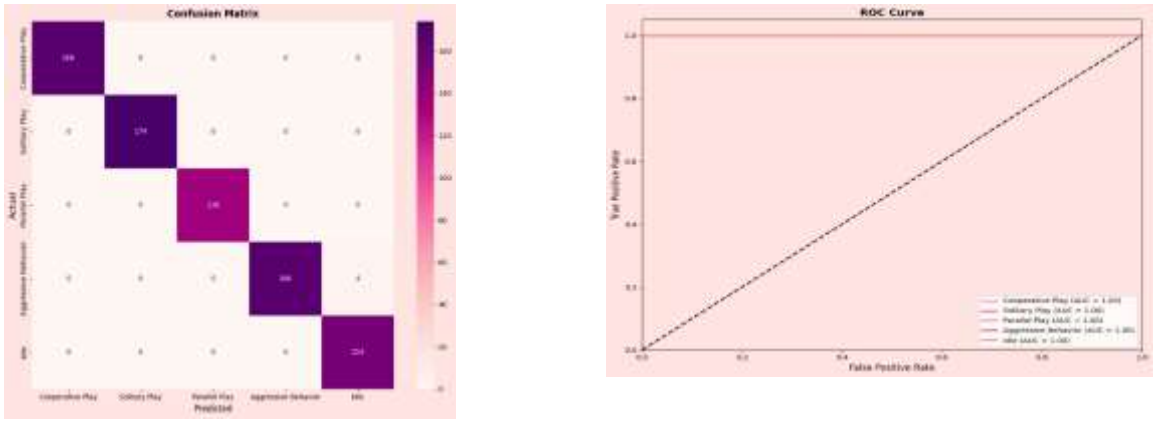
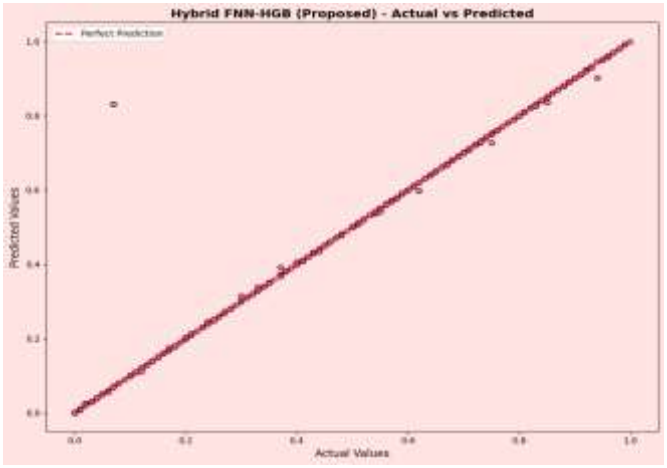


Fig. 5: Obtained confusion matrix and ROC curve of play_behavior from FNB models

Fig 5 presents the confusion matrix and ROC curve obtained from the proposed FNB model for the play_behavior classification task. The confusion matrix shows the distribution of correctly classified and misclassified samples across the behavior categories. The ROC curve illustrates the classification performance of the hybrid model by showing the relationship between true positive rate and false positive rate. The visualization highlights the improved classification capability of the proposed model in identifying player behavior patterns from the gameplay dataset.



(d)

Fig. 6: Obtained scatter plot of activity_level from FNB models

Fig. 6 presents the scatter plot obtained from the proposed FNB model for predicting activity_level. The scatter plot represents the predicted values against the actual activity levels from the dataset. The distribution of points indicates the regression performance of the hybrid model and demonstrates its effectiveness in predicting player engagement intensity from the gameplay data.

Fig. 7: Predictions on Sample Test Data using proposed FNB model

Fig. 7 illustrates the prediction results generated by the trained ML models on the test dataset. The screen displays the predicted outputs produced after processing the input gameplay features through the trained models. The system analyzes the test data attributes and generates predictions for play_behavior classification and activity_level regression. The prediction interface presents the output results in a structured format that allows users to observe the predicted behavior category and engagement intensity values for each record in the dataset. This module demonstrates the final stage of the implemented system where trained models perform behavior detection and activity level prediction based on gameplay data.

Table 1: Performance evaluation of ml models for play_behavior classification

Model	Accuracy (A)	Precision (P)	Recall (R)	F1-Score
KNN	0.6388	0.6398	0.6388	0.6383
RF	0.9175	0.9263	0.9175	0.9174
SVM	0.9875	0.9879	0.9875	0.9875
FNB (Proposed)	0.9950	0.9951	0.9950	0.9950

Table 1 presents the classification performance of different ML models used for predicting the play_behavior variable in the gameplay dataset. The performance of the models is evaluated using metrics such as Accuracy (A), Precision (P), Recall (R), and F1-Score. The KNN model records the lowest performance among the compared models with an accuracy of 0.6388. The RF model shows significant improvement with an accuracy of 0.9175. The SVM model achieves higher performance with an accuracy of 0.9875. The proposed FNB model demonstrates the highest performance with an accuracy of 0.9950 along with the best precision, recall, and F1-score values. These results indicate the effectiveness of the proposed hybrid model in accurately classifying player behavior from the gameplay dataset.

Table 2. Performance evaluation of ml models for activity_level prediction

Model	MAE	MSE	RMSE	R^2-Score
KNN	0.1717	0.0456	0.2135	0.4463
RF	0.0389	0.0113	0.1064	0.8626

SVM	0.0902	0.0090	0.0948	0.8909
FNB (Proposed)	0.0052	0.0029	0.0539	0.0539

Table 2 presents the regression performance of different ML models used for predicting the activity_level variable in the dataset. The models are evaluated using regression metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2-Score. The KNN model records higher error values and a lower R^2 score compared to the other models. The RF and SVM models show improved regression performance with lower error values and higher R^2 scores. The proposed FNB model achieves the best performance with the lowest MAE, MSE, and RMSE values along with the highest R^2 score of 0.9648. These results demonstrate the capability of the hybrid model in accurately predicting the player activity level from the gameplay data.

5. Conclusion

The proposed Game Mood Net framework represents a significant advancement in gameplay behavior analysis and emotional state detection by integrating machine learning models within a unified analytical platform. The system evaluates multiple ML approaches including KNN, RF, and SVM while introducing the proposed FNB hybrid model to improve prediction performance. A major challenge addressed in this research involves accurately modeling complex behavioral patterns present in gameplay data and reducing prediction errors in both classification and regression tasks. Comparative experimental evaluation demonstrates that the proposed FNB model consistently outperforms the baseline models across all evaluation metrics. The model achieves a classification accuracy of 99.50% for predicting play_behavior, significantly higher than KNN, RF, and SVM. In addition, the regression results for activity_level prediction show the lowest error values with an R^2 score of 0.9648, indicating strong predictive capability. The hybrid architecture effectively captures complex patterns within the dataset and produces highly reliable prediction outcomes.

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